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## Utilization of free medication samples in the United States in a nationally representative sample: 2009–2013

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#### Abstract

**Background**—Manufacturers provide free sample medications as a means to increase use of branded medications. Sample use varies year-to-year as branded product patents expire and new products come to market.

**Objective**—This study sought to describe the use of sample medications during 2009–2013 and assess individual characteristics associated with sample use.

**Methods**—Data from the 2009–2013 U.S. Medical Expenditure Panel Survey (MEPS) were used. MEPS asks participants whether they received each medication they are taking as a sample. The top 10 medications and medication classes used each year by volume were identified as well as the proportion of people who used at least one sample medication. The proportion of new initiators of medications were also classified as the percent who received a sample for the specific medication. Logistic regression was used to assess individual demographics, insurance, and medication characteristics associated with use.

**Results**—Prevalence of sample use ranged from 9.3% in 2009 to 6.2% in 2013. The most widely used sample medications included statins during 2009–2011, which changed to inhaled  $\beta$ -agonists in 2012–2013, as atorvastatin became available as a generic. The overall volume of the top 10 free sample medications decreased by one-third over this study period. In 2013, 12.6% of new insulin analog users and 11.0% of new oral contraceptive users receive these medications through samples. Regression analysis showed that U.S. Medicaid- and Medicare-insured persons were less likely to use samples compared to those with private insurance.

**Conclusions**—Sample medication use has decreased as generic medications are becoming more used in the U.S.

#### Keywords

Sample medications; Generic drugs; Pharmaceutical marketing; Physician prescribing

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#### Introduction

Free medication samples are widely disbursed to prescribers as a marketing tool for trade name products. In 2005, the total value of medications provided was approximately \$18 billion, with up to 20% of all Americans and nearly 50% of Medicare beneficiaries utilizing samples annually.<sup>1,2</sup> This practice is seen as pervasive by some medical associations and patient advocacy groups but is typically viewed positively by prescribers and patients.<sup>3,4</sup> As implied, patients receive the medications for free and avoid immediate costs of the medication at the point of care. Therapy is initiated immediately without a pharmacy visit and the prescriber has the opportunity to provide medication counseling, which can be important for certain dosage forms or devices.<sup>5</sup>

Despite the perceived benefits, pharmaceutical companies intend the practice as a means to increase use of branded medications. This can lead to increased use of more expensive branded products, which increases costs to both patients and third-party payers if the sampled medication is continued versus a suitable generic alternative.<sup>6–9</sup> Further, use of sample medications forgoes the typical process of prescribing and dispensing and removes the medication experts – pharmacists – from their roles in screening for potential drug–drug and drug–disease interactions and in providing medication counseling.<sup>10</sup>

Medication sample use is difficult to analyze as the practice circumvents the process of recording filled medications at the pharmacy or in insurance billing claims. Previous studies have utilized the U.S. Medical Expenditure Panel Survey (MEPS) to investigate sample use given that it provides a self-reported estimate of sample use in a nationally representative weighted sample.<sup>11,12</sup> These studies have looked at medication use through 2005 and have identified individual characteristics associated with sample medication patent life expires and because generic medication use has become more prevalent over the last decade. Thus, this study sought to update the information regarding sample medication use in the U.S. during the most recent five-year period available in MEPS (2009–2013). Medications used as samples were identified and the individual characteristics associated with sample use in the most recent year (2013) were also explored.

#### Methods

#### **Data sources**

MEPS data were used to estimate the scope of free sample use and to characterize the typical user. MEPS data are de-identified and publicly available and contain information on patient demographics, sources of payment, medical service and pharmaceutical medication utilization and expenditures. Due to the public and de-identified nature of these data, they are exempt from an institutional review board approval process.

#### Study population and design

Data from years 2009–2013 were used to conduct a cross-sectional study that looked at the disbursement of free medication samples in the U.S. over this time period. The most recent

#### Sample prescription medication use

MEPS provided "Prescribed Medicines" files that contain information on prescription medication use. Survey respondents are first asked about the medications they use and if they received any of these medications as free samples. Any patient that identified at least one of their medications as a free sample was considered a sample user for the study. Patients are also asked to identify if they are a new user of a particular medication for the respective year. The "Prescribed Medicines" file includes medication information for each person and Generic Product Identifier (GPI) codes (Medi-Span, Indianapolis, IN) were used to identify medications including all formulations for each medication. Using weights from expenditure files provided by MEPS, the top 10 classes of medications and top 10 medications for each year of the data from 2009 to 2013 by volume were determined as well as the percent of the population using sample medications each year. Additionally, for new users of any medications in each year, the percent of patients receiving free sample for that particular medication in the given year was reported.

#### Sample users characteristics in 2013

MEPS 2013 "Full Year Consolidated" files contained demographic information on the respondents. Race and ethnicity were combined into a single variable with the following categories: Hispanics, non-Hispanic Whites, non-Hispanic Blacks and non-Hispanics that belonged to other races. A new medical insurance indicator was created from variables available in the data, and it consisted of the following insurance provider categories: Private, Medicaid, Medicare (dual eligibles were classified in the Medicaid group), other public insurance, and uninsured. Additionally, an indicator for prescription medication insurance was included. Educational status was collapsed into two levels: lower than high school, and at least high school level. Family income, as a percentage of the annual Federal Poverty Limit (FPL), was classified for income <100% of FPL, 100 and <125% of FPL, 125% and <200% of FPL, 200% and <400% of FPL, 400% of FPL. Geographic region was based on U.S. Census regions. The total number of prescription medications used by each individual in 2013 was also calculated.

#### Statistical analyses

All statistical analyses were conducted using SAS 9.4 (Cary, North Carolina). SAS survey commands were utilized to incorporate survey weights provided by MEPS; this allows the generalization of results to represent the national population based on race, gender, age, and geographic factors. Weighted counts and frequencies are reported for patient characteristics for the year 2013. Chi-square tests were used to compare across categorical variables. A multiple logistic regression model was performed to identify factors associated with the receipt of any sample medications for 2013. This model included patient demographics, access to care variables, and the count of total prescription medications. Odds ratios and 95% CI are reported. The significance level for the study was set at a < 0.05.

#### Results

#### Medications used as samples

Over the time period 2009–2013, prevalence of sample medication use decreased in the U.S. from 9.3% in 2009 to 6.2% in 2013. Table 1 shows the top 10 individual medications and medication classes used as samples by volume. During 2009-2011, HMG Co-A reductase inhibitors ("statins") were the most widely used sample medications, with a volume of roughly 1.3 million samples each year. This group consisted mostly of rosuvastatin and atorvastatin. Statins were supplanted by inhaled  $\beta$ -agonists, as atorvastatin lost patent protection heading into 2012. Some medications widely available as generics but with branded versions were in the top 10 in 2013, such as levothyroxine. Other highly used free sample medication classes in 2013 included non-steroid anti-inflammatory drugs (NSAIDs), proton pump inhibitors (PPIs), insulin analogs, and oral contraceptives. The total volume of samples utilized in the top 10 medication classes decreased by over one-third between 2009 and 2013 (9 million to 6 million). For those under 18 years of age, asthma medications were the highest utilized classes. For non-elderly adults, more variation was present with inhaled β-agonists, anti-depressants, and statins being highly used, among others. For elderly individuals, inhaled  $\beta$ -agonists (±steroids), statins, and  $\beta$ -blockers (oral and ophthalmic) were highly utilized.

Table 2 shows the percent of people who were new initiators of each medication class who used a sample for that class. For example, in 2009, 5.2% of statin initiators used a statin sample while in 2013 only 2.8% did. In 2013, the highest initiators using samples were among insulin users (12.6%), selective norepinephrine reuptake inhibitors (SNRIs; 13.9%), and oral contraceptives (11.0%).

#### Characteristics of free sample users

Characteristics of samples users and non-users in 2013 are summarized in Table 3. The total weighted sample represented nearly 180 million people in the U.S. who filled a prescription medication. Table 4 shows the adjusted comparisons of users and non-users with adjusted odds ratios (aOR) and 95% confidence intervals (CI). Gender, age, race, prescription drug coverage, family income, and region were all non-significant predictors of sample use. Those with Medicaid (aOR = 0.63, 95% CI 0.43-0.92) or Medicare (aOR = 0.56, 95% CI 0.34-0.95) insurance were less likely to use samples compared to those with private insurance. Other public insurance and uninsured status was not associated with sample use compared to the 'Private' reference group. Those with high school or higher education had 17–98% higher odds of being sample users compared to those with less than a high school education. Also, for each additional prescription medication filled, the odds of sample used increased by roughly 1–2%. The c-statistic for the model was 0.649, showing low model discriminatory power for sample users.

#### Discussion

Year-to-year variability was observed in the medications sampled, which is associated with patent expiry and new medications coming onto the market throughout the time period.

Thus, the characteristics of free sample users are likely to change as new disease states are treated by these sampled medications. Also observed was an overall decrease in sample use as measured by the prevalence of sample users as well as the total volume of sample use. This is attributed to the increase in generic utilization (85% of all prescriptions by volume) overall in the U.S. as the number of block-bluster branded products have decreased.<sup>13</sup> Despite decreasing prevalence, sample medications have a tremendous economic impact<sup>7,14</sup> and can also influence research on products available through samples.<sup>15</sup>

Sample medications are provided as a means of pharmaceutical marketing of branded products, even when direct (i.e. same chemical entity) or therapeutic (i.e. same therapeutic class) substitutes exist.<sup>7</sup> While the practice has been defended as a means to provide medications to those without insurance,<sup>16</sup> this does not appear to be the case in this study or in previous literature,<sup>11,12</sup> and is counterintuitive, as uninsured individuals have fewer means to attain branded products once the sample supply is extinguished. Cost implications associated with this practice can impact individual out-of-pocket spending as well as third-party payer costs. This is especially concerning when low-cost generic programs are widely prevalent and provide access to affordable medications regardless of insurance.<sup>17,18</sup>

A study by Duru et al investigated the potential cost savings associated with both direct and therapeutic substitution among diabetic patients with Medicare Part D coverage.<sup>7</sup> They found that direct substitution would save approximately \$150 dollars per person and therapeutic substitution would save \$400 per person. Among the top ten medications in 2013, only levothyroxine was available as a generic. However, this is also an example where substitution may not necessarily confer equivalence, as levothyroxine products have been shown to vary in their bioavailability.<sup>19,20</sup> Other examples include warfarin, estrogens, and anticonvulants, which were also in the top 20 of all free sample drugs (data not shown).<sup>21</sup> This further highlights the marketing strategy of free sample medications, as a patient could not necessarily move from the sample branded product to a generic version without a potential dose adjustment. Therapeutic substitution implies equivalence within a class, which is arguable for a number of the Top 10 sampled classes including statins, NSAIDs, PPIs, and SNRIs.<sup>22</sup>

#### Limitations

This study is subject to some limitations. Primarily, sample use is self-reported by MEPS participants who could misunderstand the question or have recall bias, although participants are led through the survey by trained personnel. Other important medications by expenditures, such as self-injected biologics, were also observed but not reportable due to low sample sizes. The *a priori* objectives of this study were also to investigate individual access to care characteristics as well as provider characteristics that were may be predictive of sample use. However, a high number of missing responses were observed, limiting the usefulness of these variables. Further, the adjusted model showed low discriminatory power for sample users. This suggests that other individual characteristics, or prescriber characteristics, may be predictive of sample use other than those variables included here.

#### Conclusion

In the United States, 6.2% of prescription medication users used a free sample medication. The types of medications used as samples changes annually as medications patent life expires or new medications enter the market. Sample medications have tremendous cost implications, especially when direct or therapeutic generic substitutes exist.

#### Acknowledgments

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# Table 1

Top 10 sampled prescription classes and medications by volume (weighted # of users per year)

2009		2010		2011		2012		2013	
Rx group	Volume								
Statins	1,459,373	Statins	1,364,312	Statins	1,309,816	B-agonist, asthma	1,290,983	B-agonist, asthma	1,705,934
PPIs	1,059,082	B-agonist, asthma	1,208,483	B-agonist, asthma	1,440,948	Statins	994,494	Statins	735,596
B-agonist, asthma	1,130,824	Antihypertensive combos	836,541	PPIs	770,164	PPIs	650,951	NSAIDs	497,698
Nasal steroids	1,124,188	PPIs	762,551	NSAIDs	815,631	NSAIDs	609,343	PPIs	524,684
Antihypertensive combos	734,621	Oral contraceptives	956,440	Nasal steroids	875,412	Insulins	473,182	Insulins	442,751
NSAIDs	723,904	Nasal steroids	881,966	Oral contraceptives	846,058	Oral contraceptives	550,370	Oral contraceptives	561,922
Oral contraceptives	914,276	SSRIs	691,340	Insulins	374,501	Antihypertensive combos	415,763	Nasal steroids	518,105
SNRIs	857,976	ARBs	515,435	Antihypertensive combos	439,471	SNRIs	552,591	SNRIs	470,751
ARBs	643,353	NSAIDs	440,997	SNRIs	454,499	Nasal steroids	488,726	<b>B-blockers</b>	340,717
SSRIs	556,884	SNRIs	511,376	<b>B-blockers</b>	460,717	<b>B</b> -blockers	490,853	Anticonvulsants	301,552
Rx name	Volume								
Rosuvastatin	641,609	Rosuvastatin	537,287	Rosuvastatin	580,064	Fluticasone-salmeterol	476,596	Albuterol	732,089
Atorvastatin	489,553	Atorvastatin	496,329	Fluticasone-salmeterol	614,094	Rosuvastatin	424,961	Fluticasone- salmeterol	516,672
Fluticasone-salmeterol	545,694	Fluticasone-salmeterol	558,735	Albuterol	406,378	Albuterol	379,607	Rosuvastatin	464,887
Mometasone	556,378	Montelukast	403,683	Atorvastatin	392,881	Mometasone	351,132	Duloxetine	385,721
Duloxetine	562,262	Levothyroxine	530,767	Duloxetine	396,446	Simvastatin	232,605	Mometasone	424,659
Levothyroxine	501,965	Escitalopram	511,606	Montelukast	384,240	Esomeprazole	238,098	Budesonide-formoterol	321,115
Celecoxib	376,643	Albuterol	332,299	Mometasone	447,350	Duloxetine	344,132	Levothyroxine	282,589
Montelukast	378,199	Duloxetine	381,045	Esomeprazole	307,108	Celecoxib	268,679	Esomeprazole	205,705
Escitalopram	433,799	Esomeprazole	282,154	Levothyroxine	335,092	Levothyroxine	251,887	Celecoxib	197,839
Esomeprazole	310,912	Mometasone	294,925	Simvastatin	243,527	Montelukast	314,885	Tadalfil	222,098

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2009		2010		1107		2012		2013	
Drug class	%	% Drug class	%	% Drug class	%	Drug class	%	% Drug class	%
Statins	5.2	5.2 Statins	4.7	Statins	3.7	B-agonists, asthma	7.1	7.1 B-agonists, asthma	10.6
PPIs	8.8	B-agonists, asthma	9.4	B-agonists, asthma	<i>T.</i> 7	Statins	4.4	Statins	2.8
B-agonists, asthma	8.7	Antihypertensive combos	8.7	PPIs	6.4	PPIs	5.0	5.0 NSAIDs	1.7
Nasal steroids	17.1	PPIs	6.5	NSAIDs	4.5	NSAIDs	2.6	PPIs	4.4
Antihypertensive combos	11.5	11.5 Oral contraceptives	12.4	Nasal steroids	12.9	12.9 Insulin	9.1	Insulin	12.6
NSAIDs	3.3	Nasal steroids	13.3	Oral contraceptives	13.1	Oral contraceptives	8.1	Oral contraceptives	11.0
Oral contraceptives	13.3	SSRIs	6.4	Insulin	4.9	Antihypertensive combos	5.6	Nasal steroids	7.5
SNRIs	26.0	ARBs	9.1	Antihypertensive combos	5.6	SNRIs	11.0	SNRIs	13.9
ARBs	25.0	25.0 NSAIDs	2.0	SNRIs	15.6	15.6 Nasal steroids	8.0	Beta-blockers	3.6
SSRIs	5.2	5.2 SNRIs	13.9	Beta-blockers	3.9	3.9 Beta-blockers	5.5	Anticonvulsants	4.8

Table 3

Characteristics of sample users and non-users in 2013

	Received at le	ast one samp	Received at least one sample medications	Did not receiv	/e any samp	Did not receive any sample medication
	N	Row %	Column %	Ν	Row %	Column %
Overall	11,762,789	6.2	100	177,964,962	93.8	100
Gender						
Male	4,818,923	5.8	41.0	78,765,783	94.2	44.3
Female	6,943,866	6.5	59.0	99,199,179	93.5	55.7
Age categories $^{**}$						
Less than 18 years	1,076,950	3.2	9.2	32,740,466	96.8	18.4
18–34 years	1,499,175	4.5	12.7	31,884,446	95.5	17.9
35–64 years	5,847,096	7.2	49.7	75,677,991	92.8	42.5
65–74 years	1,788,051	7.7	15.2	21,442,940	92.3	12.0
75 years and above	1,551,517	8.7	13.2	16,219,118	91.3	9.1
Race						
non-Hispanic Whites	8,454,042	6.4	71.9	122,954,217	93.6	69.1
Hispanics	1,387,691	5.7	11.8	23,097,766	94.3	13.0
non-Hispanic Blacks	1,187,382	5.7	10.1	19,696,885	94.3	11.1
non-Hispanic Asians	427,291	5.7	3.6	7,016,792	94.3	3.9
non-Hispanic others	306,385	5.6	2.6	5,199,301	94.4	2.9
Medical insurance coverage $^*$						
Private insurance	6,74,6762	6.0	57.4	105,103,285	93.9	59.1
Medicaid	896,330	3.8	7.6	2,254,5332	96.2	12.7
Medicare	482,532	7.9	4.1	5,63,9400	92.1	3.2
Other public insurance	268,733	5.5	2.3	4,58,6131	94.5	2.6
Uninsured	1,18,2764	8.1	10.1	13,37,4713	91.9	7.5
Prescription drug insurance coverage						
No coverage	1,54,3776	7.9	13.1	18,03,5458	92.1	10.1
Had prescription drug coverage	10,19,9079	6.0	86.7	158,704,468	93.9	89.2
Educational status						
Less than high school	2,536,571	4.9	21.6	49,696,269	95.1	27.9

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N     Row %     Column %     N     Row %     Column %       school and higher     8,820,674     7.1     75.0     115,975,717     92.9       ag     405,545     3.2     3.2     3.4     12,292,976     96.8       bf     1,479,221     5.8     12,292,976     96.8     94.2       bf     1,479,221     5.8     12,6     24,081,788     94.2       bf     1,917,262     7.6     16.3     23,434,432     94.0       bf     3,323,661     6.0     28.3     51,736,455     94.0       bf     3,323,561     6.0     23,434,32     94.0     94.0       bf     2,333,464     33.6     94.0     94.0     94.0       bf     2,131,535     59.4     94.0 <td< th=""><th></th><th><b>Received at least one sample medications</b></th><th>ast one samp</th><th>le medications</th><th>Did not receive any sample medication</th><th><u>че ану samp</u></th><th>ie illeuication</th></td<>		<b>Received at least one sample medications</b>	ast one samp	le medications	Did not receive any sample medication	<u>че ану samp</u>	ie illeuication
5747.175.0 $115,975,717$ $92.9$ 5453.23.4 $12.292,976$ $96.8$ 2215.8 $12.6$ $24,081,788$ $94.2$ 2215.8 $12.6$ $24,081,788$ $94.2$ 2017.0 $5.3$ $8,304,644$ $93.0$ 2627.6 $16.3$ $23,434,432$ $92.4$ 561 $6.0$ $28.3$ $51,736,455$ $94.0$ 553 $5.9$ $37.5$ $70,407,643$ $94.1$ 564 $18.2$ $31,531,686$ $93.6$ 770 $6.0$ $21.7$ $40,241,534$ $94.0$ 91 $7.0$ $42.1$ $66,143,817$ $93.0$ 51 $70,80,974$ $94.0$ $93.0$ 92 $5.1$ $17.9$ $38,789,974$ $94.0$ 93 $6.9$ $1.70$ $42.1$ $66,143,817$ $93.0$ 94 $6.0$ $21.7$ $40,241,534$ $94.0$ 95 $1.0$ $17.9$ $38,789,974$ $94.0$ 95 $1.0$ $17.9$ $38,789,974$ $94.9$ 95 $1.0$ $10$ $10$ $10$ 95 $6.5-38$ $6.9$ $1.8-19.7$		Ν	Row %	Column %	Ν	Row %	Column %
545   3.2   3.4   12,292,976   96.8     221   5.8   12.6   24,081,788   94.2   1     291   7.0   5.3   8,304,644   93.0   1     261   6.0   5.3   8,304,644   93.0   2     561   6.0   28.3   51,736,455   94.0   2     555   5.9   37.5   70,407,643   94.1   3     355   5.9   37.5   70,407,643   94.1   3     402   6.0   28.3   31,531,686   93.6   1     402   6.0   21.7   40,241,534   94.0   2     710   6.0   21.7   40,241,534   94.0   2     91   7.0   6.0   21.7   40,241,534   94.0   2     91   7.0   6.9   42.1   64.9   2   3     6.9   6.5   5.1   17.9   38,789,974   94.0   2     833   5.1   17.9   38,789,974   94.9   2   3     84	At least high school and higher	8,820,674	7.1	75.0	115,975,717	92.9	65.2
215.812.6 $24,081,788$ $94.2$ 2917.05.3 $8,304,644$ $93.0$ 2627.616.3 $2,3,434,432$ $92.4$ 5616.0 $28.3$ $51,736,455$ $94.0$ 5555.9 $37.5$ $70,407,643$ $94.1$ 4926.4 $18.2$ $31,531,686$ $93.6$ 7706.0 $21.7$ $40,241,534$ $94.0$ 917.0 $42.1$ $66,143,817$ $93.0$ 517.0 $42.1$ $66,143,817$ $93.0$ 517.0 $6.0$ $21.77$ $40,241,534$ $94.0$ 917.0 $6.0$ $21.77$ $40,241,534$ $94.0$ 925.1 $17.9$ $38,789,974$ $94.9$ 101102 $Median$ $1QR$ 6.9 $6.5-38$ $6.9$ $1.8-19.7$	Status missing	405,545	3.2	3.4	12,292,976	96.8	6.9
221 $5.8$ $12.6$ $24,081,788$ $94.2$ 291 $7.0$ $5.3$ $8.304,644$ $93.0$ 262 $7.6$ $16.3$ $23,43,432$ $92.4$ 561 $6.0$ $28.3$ $51,736,455$ $94.0$ 553 $5.9$ $37.5$ $70,407,643$ $94.1$ 564 $6.0$ $28.3$ $31,531,686$ $93.6$ 570 $6.0$ $21.7$ $40,241,534$ $94.0$ 901 $7.0$ $21.7$ $40,241,534$ $94.0$ 59 $5.1$ $17.9$ $38,789,974$ $94.9$ 60 $6.5-38$ $5.6,143,817$ $93.0$ 61 $1QR$ $Redian$ $1QR$	Poverty status						
201   7.0   5.3   8,304,644   93.0     262   7.6   16.3   23,434,432   92.4     561   6.0   28.3   51,736,455   94.0     555   5.9   37.5   70,407,643   94.1     556   6.0   28.3   51,736,455   94.0     557   5.9   37.5   70,407,643   94.1     700   6.0   21.7   40,241,534   94.0     710   6.0   21.7   40,241,534   94.0     91   7.0   42.1   66,143,817   93.0     921   7.0   42.1   66,143,817   93.0     930   5.1   17.9   38,789,974   94.9     160   1.0   42.1   66,143,817   93.0     6.9   6.5-38   5.1   1.8-19.7   94.9	<100% of FPL	1,479,221	5.8	12.6	24,081,788	94.2	13.5
2627.616.3 $23,43,4,32$ $92.4$ 5616.0 $28.3$ $51,736,455$ $94.0$ 555 $5.9$ $37.5$ $70,407,643$ $94.1$ 555 $5.9$ $37.5$ $70,407,643$ $94.1$ 492 $6.4$ $18.2$ $31,531,686$ $93.6$ 770 $6.0$ $21.7$ $40,241,534$ $94.0$ 91 $7.0$ $42.1$ $66,143,817$ $93.0$ 50 $5.1$ $17.9$ $38,789,974$ $94.9$ 1imIQR $\mathbf{Medim}$ IQR $6.9$ $6.5-38$ $6.9$ $1.8-19.7$	100 and < 125% of FPL	627,291	7.0	5.3	8,304,644	93.0	4.7
6016.028.351,736,45594.03555.937.570,407,64394.14926.418.231,531,68693.67706.021.740,241,53494.0917.042.166,143,81793.05171938,789,97494.910117.938,789,97494.91117.938,789,97494.91110R6.01.8-19.76.96.5-386.91.8-19.7	125 and $< 200%$ of FPL	1,917,262	7.6	16.3	23,434,432	92.4	13.2
55 5.9 37.5 70,407,643 94.1   492 6.4 18.2 31,531,686 93.6   770 6.0 21.7 40,241,534 94.0   91 7.0 42.1 66,143,817 93.0   539 5.1 17.9 38,789,974 94.9   160 42.1 66,143,817 93.0   63 6.5 38,789,974 94.9	200  and < 400%  of FPL	3,323,661	6.0	28.3	51,736,455	94.0	29.1
492 6.4 18.2 31,531,686 93.6   770 6.0 21.7 40,241,534 94.0   991 7.0 42.1 66,143,817 93.0   539 5.1 17.9 38,789,974 94.9   fian IQR Median IQR   6.9 6.5-38 6.9 1.8-19.7	400% of FPL	4,415,355	5.9	37.5	70,407,643	94.1	39.6
492 6.4 18.2 31,531,686 93.6   770 6.0 21.7 40,241,534 94.0   991 7.0 42.1 66,143,817 93.0   535 5.1 17.9 38,789,974 94.9   536 5.1 17.9 38,789,974 94.9   541 17.9 38,789,974 94.9   551 17.9 38,789,974 94.9   69 6.5-38 6.9 1.8-19.7	Region						
770 6.0 21.7 40,241,534 94.0   991 7.0 42.1 66,143,817 93.0   533 5.1 17.9 38,789,974 94.9   fian IQR Median IQR   6.9 6.5-38 6.9 1.8-19.7	Northeast	2,138,492	6.4	18.2	31,531,686	93.6	17.7
901 7.0 42.1 66,143,817 93.0   539 5.1 17.9 38,789,974 94.9   ian IQR Median IQR   6.9 6.5–38 6.9 1.8–19.7	Midwest	2,555,770	6.0	21.7	40,241,534	94.0	22.6
539 5.1 17.9 38,789,974 94.9   ian IQR Median IQR   6.9 6.5–38 6.9 1.8–19.7	South	4,949,091	7.0	42.1	66,143,817	93.0	37.2
lian IQR Median 6.9 6.5–38 6.9	West	2,100,639	5.1	17.9	38,789,974	94.9	21.8
6.9 6.5–38 6.9	Number of prescriptions per person	Median	IQR		Median	IQR	
FPL = Federal poverty limit; IQR interquartile range. P < 0.05; P < 0.0001. =		16.9	6.5–38		6.9	1.8 - 19.7	
P < 0.05; P < 0.0001. =	FPL = Federal poverty limit; IQR interqu	artile range.					
P = 0.0001. =	$^{*}_{P < 0.05};$						
	P < 0.0001. =						

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#### Table 4

Results of multiple logistic regression predicting use of sample medications in 2013

	0 1	-	
	Adjusted odds ratio	95% CI	P-value
1	Ref.	Ref.	Ref.
	1.14	0.96, 1.36	0.1481
ories			
n 18 years	Ref.	Ref.	Ref.
ears	0.81	0.50, 1.30	0.3835
ears	1.10	0.73, 1.68	0.6453
ears	1.16	0.72, 1.87	0.5504
and above	1.27	0.73, 2.22	0.3918
panic Whites	Ref.	Ref.	Ref.
cs	1.19	0.94, 1.51	0.1428
panic Blacks	0.89	0.73, 1.10	0.2958
	1.15	0.77, 1.72	0.4864
,	0.92	0.53, 1.58	0.7527
surance coverage			
nsurance	Ref.	Ref.	Ref.
d (	0.63	0.43, 0.92	0.0155
e (	0.56	0.34, 0.95	0.0303
blic insurance	0.88	0.52, 1.49	0.6205
ed	1.19	0.80, 1.77	0.3909
n drug insurance coverage			
ļ	Ref.	Ref.	Ref.
(	0.74	0.52, 1.03	0.0759
l status			
n high school	Ref.	Ref.	Ref.
high school and higher	1.52	1.17, 1.98	0.0021
issing	1.03	0.62, 1.72	0.9089
tus (family income)			
of FPL	Ref.	Ref.	Ref.
d <125% of FPL	1.00	0.68, 1.47	0.9876
d <200% of FPL	1.07	0.74, 1.55	0.7291
d <400% of FPL	0.81	0.56, 1.17	0.2656
of FPL	0.83	0.58, 1.17	0.2847
st	Ref.	Ref.	Ref.
. (	0.98	0.69, 1.41	0.9261
	1.18	0.87, 1.62	0.2898
	0.82	0.58, 1.18	0.2873
of FPL (	0.83 Ref. 0.98 1.18	0.58, 1.17 Ref. 0.69, 1.41 0.87, 1.62	0.28 Ref. 0.92 0.28

	Adjusted odds ratio	95% CI	P-value
Number of prescriptions	1.02	1.01, 1.02	< 0.0001

FPL = federal poverty limit; CI = confidence interval.

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